

# Hyperplane separation theorem and intro to convex analysis

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## Theorem

Definition: If  $C_1, C_2 \subseteq \mathbb{R}^n$  are nonempty, convex and disjoint ( $C_1 \cap C_2 = \emptyset$ ), then there exists a hyperplane  $H \subset \mathbb{R}^n$  such that  $H$  separate  $C_1$  and  $C_2$ .

- Convex
- Hyperplane
- Separate

## Convexity

A set  $S$  is convex in  $\mathbb{R}^n$  iff  $\forall x, y \in S, l(x, y) \in S$ . Where  $l(x, y) = \{\lambda x + (1 - \lambda)y : \lambda \in [0, 1]\}$ .

Theorems about convexity: Given  $C_1$  and  $C_2$  convex,

- $C_1 \cap C_2$  is convex
- $C_1 + C_2$  is convex
- $C_1 + v$  is convex
- $AC_1$  is convex, where  $A$  is a matrix

## Hyperplane

Definition: A hyperplane is a flat in  $\mathbb{R}^n$  with dimension  $n - 1$ .

Definition for flat and its dimension:

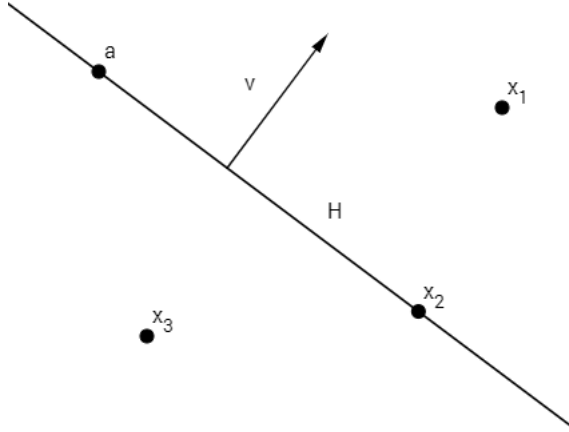
$F$  is a flat of dimension  $k$  iff  $F = W + v$  for some  $v \in \mathbb{R}^n$  and  $W \leq \mathbb{R}^n$  such that  $\dim(W) = k$ .

Theorems about Hyperplanes and flats:

- Every flat is convex, and so is hyperplanes and subspaces.

- A hyperplane can be represented by a perpendicular vector and a arbitrary point on the hyperplane. In this case,  $H(v, a) = \{x \in \mathbb{R}^n : \langle v, x - a \rangle = 0\}$
- A hyperplane can also be represented by a linear functional and a scalar where:  $H(f, t) = \{x \in \mathbb{R}^n : f(x) = t\}$

## Separation



Example in  $\mathbb{R}^2$ , we know that:

- $v \cdot (x_1 - a) > 0$
- $v \cdot (x_2 - a) = 0$
- $v \cdot (x_3 - a) < 0$

In general, hyperplane  $H = (v, a)$  can separate the whole space into:

- $\{x \in \mathbb{R}^n : \langle v, x - a \rangle > 0\}$
- $\{x \in \mathbb{R}^n : \langle v, x - a \rangle = 0\} = H$
- $\{x \in \mathbb{R}^n : \langle v, x - a \rangle < 0\}$

We say that  $H$  separates two half spaces defined as:

$$C_{\geq} = \{x \in \mathbb{R}^n : \langle v, x - a \rangle \geq 0\}$$

$$C_{\leq} = \{x \in \mathbb{R}^n : \langle v, x - a \rangle \leq 0\}$$

Notice that the second notation of hyperplane  $H(f, t)$  is closely related with the first one with the following correspondence:  $t = \lambda \langle v, a \rangle$  and  $f(x) = \lambda \langle v, x \rangle$  where  $\lambda$  is a nonzero real number. So we can also define:

$$C_{\geq} = \{x \in \mathbb{R}^n : f(x) \geq t\}$$

$$C_{\leq} = \{x \in \mathbb{R}^n : f(x) \leq t\}$$

We say that a hyperplane  $H$  support a set  $S$  if and only if either  $S \subseteq C_{\geq}$  or  $S \subseteq C_{\leq}$ . Otherwise we say that  $H$  cut  $S$ .

- If  $H$  cut  $S$ , then  $S \cap H \neq \emptyset$
- If a hyperplane  $H$  supports a flat  $F$ , then  $F \subseteq H$
- If  $C$  is convex and  $x \notin C$ , then there exists a hyperplane  $H$  such that  $x \in H$  and  $H$  support  $C$ . In addition, if  $C$  is either closed or open, we can find one that is also disjoint with  $C$ . (Proof by induction on dimension)

## Proof

Because  $C_1 \cap C_2 = \emptyset$ , then  $0_v \notin C_1 - C_2$ . Notice that  $C_1 - C_2$  is convex and  $0_v \notin C_1 - C_2$ , so there is a hyperplane  $H$  such that  $0_v \in H$  and  $H$  support  $C_1 - C_2$ . So we can denote  $H = (f, 0)$  in our second notion. So, either  $f(C_1 - C_2) \leq 0$  or  $f(C_1 - C_2) \geq 0$ . Without loss of generality, suppose that  $f(C_1 - C_2) \leq 0$ . Then,  $f(C_1) \leq f(C_2)$ , so there is a lower bound for  $f(C_2)$  because  $f(C_1)$  is not empty. Let  $m$  be the greatest lower bound, so  $f(C_1) \leq m \leq f(C_2)$ . This means that hyperplane  $(f, m)$  separates  $C_1$  and  $C_2$ .

## Usage

- Farkas' lemma: Let  $A \in M_{m \times n}(\mathbb{R})$  and  $b \in \mathbb{R}^m$ , then exactly one of the following two sets of equalities/inequalities has a solution,
  1.  $Ax = b$  and  $x \geq 0$
  2.  $A^T y \geq 0$  and  $b^T y < 0$
- Strong duality theorem in linear programming: If  $P$  is a linear programming with an optimal value, then its dual has the same optimal value.

## Notation

- Let  $A, B$  be set, then  $A + B = \{a + b : a \in A, b \in B\}$   
Let  $v$  be a vector, then  $A + v = A + \{v\} = \{a + v : a \in A\}$
- Let  $v$  be a vector, then we say that  $v \geq 0$  if and only if every component of  $v$  is nonnegative. We say that  $v \leq 0$  if and only if every component of  $v$  is nonpositive. We say that a vector  $v_1 \leq v_2$  iff  $v_1 - v_2 \leq 0$  and  $v_1 \geq v_2$  iff  $v_1 - v_2 \geq 0$